Visual Analysis of User Behaviour in Pay-Per-Bid Auctions

Walker, Rick; Ap Cenydd, Llyr; Pop, Serban; Roberts, Jonathan C.

International Workshop on Visual Analytics

DOI:
http://dx.doi.org/10.2312/PE/EuroVAST/EuroVA11/025-028

Published: 01/02/2011

Peer reviewed version

International Workshop on Visual Analytics (2011)
S. Miksch and G. Santucci (Editors)

Visual Analysis of User Behaviour in Pay-Per-Bid Auctions

Rick Walker, Llyr ap Cenydd, Serban Pop and Jonathan C. Roberts

School of Computer Science, Bangor University, UK

Abstract

In pay-per-bid auctions, placing a bid costs a fee, and only raises the price of the item by a small increment. At the conclusion of the auction, the last bidder wins, and the price paid by the winning bidder is subsidised by the bidding fees paid by unsuccessful bidders. In this short paper, the first publicly available analytics of data from a pay-per-bid website are presented. We present a visual analysis approach using a specific tool developed for the purpose. This dataset represents a difficult challenge because it is huge, it is difficult to evaluate in practice even using auction theory since there exists no mathematically optimal strategy for successful bidding, and non-trivial patterns are sought.

Categories and Subject Descriptors (according to ACM CCS): H.5.0 [Information Interfaces and Presentation]: —

1. Introduction

Many of the successful Internet companies such as eBay, Amazon and Google support business models that were largely not possible before the widespread adoption of the Internet. eBay dominates the auction field to the point where it is used by economists to compare with theoretical auction findings [RO02]. eBay uses proxy bidding, which has been studied extensively.

More recently, a new auction business model has arisen: the pay-per-bid auction or, more colloquially, a penny auction. In this model, an item is initially offered by the site at a low starting price. Each bid placed raises the price of the item by a small increment and costs the bidder a small amount of money. The auction is won by the bidder who places the final bid, who must then pay the current price of the item. This process is made clearer with an example: a camera with a retail price of £300 is offered for sale at an initial price of £1. Each bid costs £1 and raises the price of the item by £0.20. At the end of the auction, 450 bids have been made, at a total cost of £450. The final price of the item is $£(1+450\times 0.20) = £91$. The site earns a profit of $£(91+450-300) = £241$ on the item (80% of its retail price) and the winning bidder makes a saving of £209, minus the price of the bids he or she placed. The other bidders receive nothing.

The ideal strategy is to place a single bid at the very end of the auction. However, each bid extends the time of the auction, so guaranteeing the last bid is not possible. There is no optimal strategy based on the rules of the system. Thus, the analysis of this data is complex: it is a huge dataset and non-trivial patterns are sought.

We propose a visual analytic solution; whereby the researcher can view the data visually, explore different scenarios, they can drill down into the data to display quantitative results and explore several hypothesis. This paper presents an analysis of user success, we first visualize the data using traditional techniques, which do not allow us to understand the data fully, thus we present a new tool for behavioural analysis in individual auctions, which enables us to initiate new insight into the data.

2. Related Work

Since pay-to-bid auctions represent a relatively new business model and consequently there is a significant lack of research focused on these specific systems, especially in the visual domain. However, there has been some analysis of other auction sites, and there has been some work that statistically analyses auctions with accompanying visual depictions.

Several researchers have collected data by scraping the Swoopo website [Aug09, PPT10, BMZ10]. They have analysed auction-level information (winner, number of bids placed, item and so on), but are less certain about bid-level data. In fact, Byers et al. [BMZ10] state that in situations where several automated bidding agents provided by the site are operating, they are unable to track all bids, and they exclude such auctions from their analysis. Although this certainly simplifies the analysis, it weakens the generality of their conclusions substantially.

Our work differs from these researchers in two important ways: first, the data used is provided directly by the site operator and is both complete (every bid in every auction) and much richer (additional information not shown to users is also available). This allows much stronger conclusions about behaviour to be drawn. Furthermore, while the site considered falls into the general category of pay-per-bid auction sites, the model operated differs from most other pay-per-bid sites. Users must buy bids before they can use them at auction, and bids can be bought directly from the site or through a pay-per-bid auction. Bids, then, operate as a virtual currency within the site, and the market price for a bid fluctuates over time. Second, the focus of this work is solely on analysing user behaviour in real data through visual means.

There are many examples of visual analysis of temporal datasets, for instance, Wongsuphasawat and Shneiderman [WS09] present a strategy and visualization method to compare across different categorical datasets. However there has been little interactive visual analysis performed on auction data. Some work has been achieved to statistically analyse auction data and depict it through scatter plots, tree-maps and other static visual depictions [SJ05, HJS06].

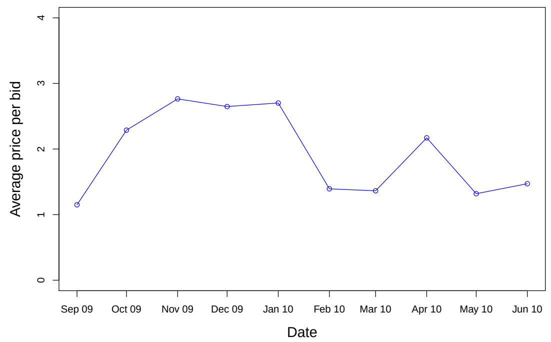


Figure 1: *Average bid prices by month. The price of bids initially rose steeply - the low initial price was due to free bids awarded to early signups and then stabilised towards the end of the year. The impact of this variable pricing is visible in user behaviour, as discussed in Section 6.*

3. Data Description

The data for this project was provided under agreement with the site operators for a total of 1,626 auctions and 732,061 bids, from September 2009 to June 2010. The data was provided with anonymised user login times and a list of auctions that each user was bidding in. For reasons of commercial sensitivity, the site is not identified in this paper. The site itself operates broadly as described in Section 1. In common with many other sites, an automated bidding agent allows users to automate their bidding process by providing a start price, a maximum end price and the number of bids to place.

Bids can be purchased in two ways: either directly from the site at a fixed price, or through a pay-per-bid auction for a pack of bids, using bids already purchased. This virtual currency system complicates the system considerably. In auctions, each user may have paid a different amount for each bid they place. In fact, the average price of bids won at auction is 1.3 while the price of bids purchased directly is 3.3. The situation is further complicated by lagniappe bids — additional free bids awarded to a user. Combining these two affects gives an adjusted price-per-bid over time as shown in Figure 1.

4. User Analytics

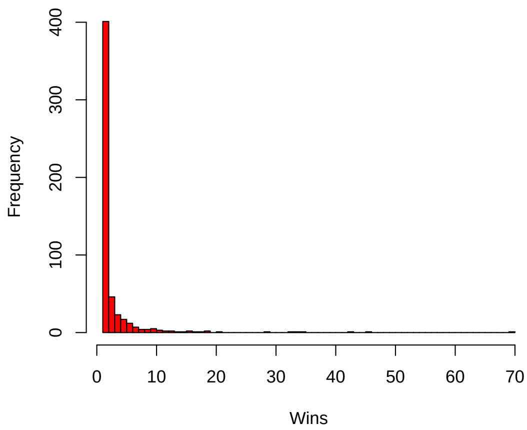


Figure 3: *Histogram of number of auction wins for the 542 users (from a total of 8,097) who have won at least one auction. While most users in this group win only once, the mean is 2.92 wins and the standard deviation is 5. Hence, a small number of users win a significantly larger number of auctions, and in fact one user has 70 wins in this dataset.*

The distribution of wins for the data is shown in Figure 3. Most users of the site have won no auctions, then from one win onwards the frequency of occurrence seems to undergo exponential decay. It is startling, though, to note that the top twenty users (less than one percent of total) have won 31% of auctions. Clearly, there are differences in auction win rates. To quantify these differences, it is helpful to define a metric for success rate.

The most obvious definition of a success rate in an auction system would be wins/auctions bid in. In a pay-per-bid auction, this is problematic because fees are paid for each bid,

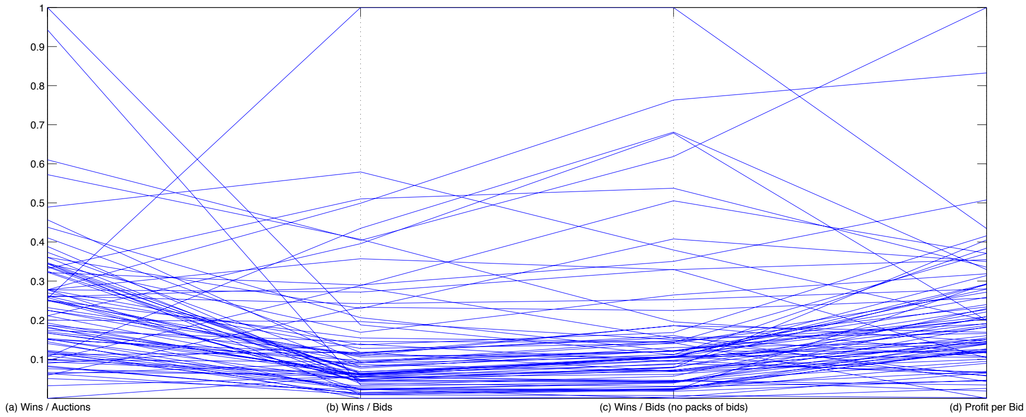


Figure 2: *Possible candidates for success metrics: (a) wins over auctions, (b) wins over bids placed (c) wins over bids placed ignoring bids and wins on auctions for packs of bids, and (d) profit per bid. Each is normalised to the range 0-1.*

not for each auction entered. Another possibility is wins/total bids placed. By this definition, successful users are those who use their bids efficiently. However, this definition neglects the affect of the virtual currency: since packs of bids can be bought at auction (the virtual equivalent of selling money at a profit), it can be argued that both bids placed and wins in auctions for packs of bids should be excluded from this calculation. A more economic slant on the situation would consider profit to the user from his or her bidding habits. To calculate this, for each user, for each auction won, the final price paid for the item and the cost of the bids used to win it are subtracted from the retail price of the item. Summing these profits for each user and dividing by the total number of bids placed gives yet another success ratio. The values of these four metrics for users with more than 3 wins are shown in Figure 2.

5. Auction Visual Analysis Tool

An interactive auction analysis tool was developed for this work to support the analytic process. An example visualization produced by this tool is shown in Figure 4. Starting at the top left, each new participating bidder is given a unique row, with successive bids represented as nodes progressing horizontally along the auction timeline. Each node is coloured by bid type - manual, auto bid, manual bonus or auto bid lagniappe.

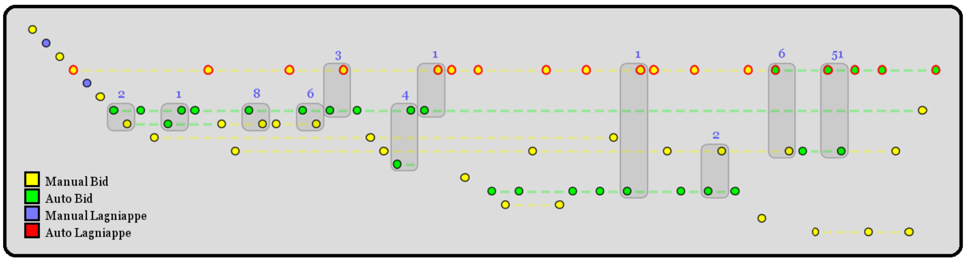
The tool allows for interactive scrolling and zooming, which facilitates intuitive navigation of the data. One of the challenges is that the repeated bidding patterns waste space. Thus, when zoomed out, repeated bidding patterns up to a set depth are automatically abstracted and labelled by the number of repetitions, thereby compressing the visualization.

The tool also allows filtering of auctions by bidder and winner id. This allows the comparison of bidding patterns between individual auctions, and hence can help identify the evolution of bidding strategies by tracking a single user over time.

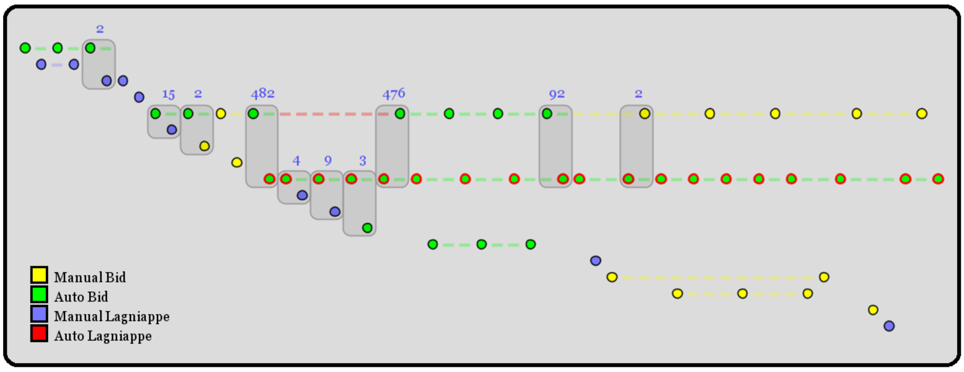
6. Visual Analysis of Strategies and Tactics

This tool has been used to glean some fascinating insights into strategic and tactical changes in behaviour by examining a successful user (named X). With a profit per bid of more than 6, X has a total of 46 wins. Moreover, X's behaviour over multiple auctions and within individual auctions shows a clear evolution over time. Initially, X wins low-to-mid value items such as compact cameras and games consoles. X begins auctions using manual bids to attempt to gauge the level of competition, then switches to the automated bidding agent only at the conclusion. But over time, a shift is observable away from this mixed tactic to the use of the automated agent throughout the entire auction, and from low value wins to higher value items such as DSLR cameras and laptops. Our tool visualizes this trend in Figure 4.

This shift seems counter-intuitive - moving from a more advanced set of tactics to a simpler one - but by also examining X's behaviour over multiple auctions, elements of a pattern become visible. The first of these is that 29 of X's 46 wins are for packs of bids sold at auction. This has the effect of substantially reducing the cost per bid in accordance with Figure 1. The second is that X bids on multiple items at the same time, and the previous mixed strategy cannot be employed in this case. In fact, towards the end of the data set available, X's strategy is to win five or six packs of bids first and then bid on (and win) one high value item before repeating the process. Aggressive bidding on these packs of



(a)



(b)

Figure 4: *Auction behaviour for user X. Bids are shown as circles coloured by type, and the auction time runs from left to right. Bids from a user are shown along the same horizontal line, X's bids are shown outlined in red, and the numbers and shaded rectangles indicate repeated bidding patterns. (a) shows an auction win from early March. X initially bids manually before switching to the automated bidding agent for the final stages of the auction. (b) shows an auction win from late May. Here, X uses the automated agent for the entire auction - a tactical change made possible by a reduced cost of bids, achieved by a strategic switch to obtaining bids at auction. This tactic also allows X to bid simultaneously in several auctions.*

bids also has the effect of increasing the average bid price for other users, by reducing the availability of cheaper bids.

7. Conclusions and Future Work

While this paper presents preliminary results of a continuing project, some initial conclusions can be drawn. Trends of the data, such as the evolving strategy and changing tactics of person X (Section 6) were only discovered through a strategic, interactive visual analysis of the data. It was important to generate a visualization that works at different levels of abstraction, and methods to compare and highlight and search different people and bid types was important.

There are still many challenges, including the visualization and analysis of the virtual currency, a look at timing and sequences of auctions and an analysis of the impact of user reputation on auction behaviour. Finally, there are many commercial implications for this analysis such as visualizing fraudulent behaviour.

References

[Aug09] AUGENBLICK N.: Consumer and Producer Behavior in the Market for Penny Auctions: A Theoretical and Empirical Analysis. *Job Market Paper. Available at* `http://www.stanford.edu/~ned789` (2009). 1

[BMZ10] BYERS J., MITZENMACHER M., ZERVAS G.: Information asymmetries in pay-per-bid auctions. In *Proc 11th ACM conf. Electronic commerce* (2010), ACM, pp. 1–12. 1

[HJS06] HYDE V., JANK W., SHMUELI G.: Investigating concurrency in online auctions through visualization. *The American Statistician 60* (August 2006), 241–250. 2

[PPT10] PLATT B. C., PRICE J., TAPPEN H.: *Pay-to-Bid Auctions*. NBER Working Papers 15695, National Bureau of Economic Research, Inc, 2010. 1

[RO02] ROTH A., OCKENFELS A.: Last-minute bidding and the rules for ending second-price auctions: Evidence from eBay and Amazon auctions on the Internet. *American Economic Review 92*, 4 (2002), 1093–1103. 1

[SJ05] SHMUELI G., JANK W.: Visualizing online auctions. *J. of Comp. Graph. Stat. 14* (2005), 299–319. 2

[WS09] WONGSUPHASAWAT K., SHNEIDERMAN B.: Finding comparable temporal categorical records: A similarity measure with an interactive visualization. In *2009 IEEE Symposium on Visual Analytics Science and Technology* (Oct. 2009), IEEE, pp. 27–34. 2